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Neighboring effects of deforestation: a spatial econometric approach

Abstract

This paper analyzes the spatial determinants of deforestation in 24 Sub-Saharan African countries during the period spanning 1990 to 2004. The general spatial two stage least squares results suggest that deforestation in one country is positively correlated to deforestation in neighboring countries. Moreover, the findings suggest that the determinants of forest clearing are region specific. Finally, the author finds enough statistical evidence to conclude that ignoring spatial correlation would significantly underestimate the effects of the driving forces of deforestation. In light of these results, the author suggests a regional cooperation when policymakers decide to fight deforestation.

Keywords: deforestation, international development, spatial correlation, Sub-Saharan Africa.
JEL Classifications: C21, O13, O55, Q23.

Introduction

In Sub-Saharan Africa (SSA), there are reasons to believe that uncontrolled deforestation is a serious issue. The upward trend in deforestation rates of the region calls for concern because estimates suggest that deforestation and forest degradation are the second largest source of global emissions of greenhouse gas after fossil fuel (Sir Nicholas Stern, 2007). With the ongoing climate change, which effects are supported by scientific evidence, the benefits provided by forest through its ecological functions cannot be overstated. Moreover, estimates provided by the International Panel on Climate Change (IPCC, 2007) suggest that tropical regions represent 80 percent of the world potential to conserve and sequester carbon. Admittedly, many environmental forums held at the international level (i.e. the 1992 Rio Earth Summit, the 1994 United Nations convention to combat desertification) reflect the concerns over tropical deforestation. In spite of these concerns, human activities continue to threaten the world forests. For example, a 2005 report by the Food and Agriculture Organization of the United Nations (FAO) documents that about 13 million hectares of the world's forests are slashed every year. At the same time, reforestation and afforestation have reduced the net loss of forest area. The world net annual conversion of forests to other land uses was 8.9 million hectares from 1990 to 2000 and 7.3 million hectares from 2000 to 2005. However, these global statistics hide some regional disparities. For example, the top ten countries with the highest rates of deforestation between 2000 and 2005 had a combined net forest loss of 8.2 million hectares. At the same time, other countries reforested about 5.1 million hectares of land. Clearly, not all countries are converting forests to other land use. Moreover, different theories are put forward to elucidate the causes of deforestation. Existing studies investigate this issue in a purely cross-sectional framework due to data availability[1] and their desire to include as many explanatory variables as they can. By doing so, they fail to account for the dynamic nature of forest clearing. Therefore, they miss the opportunity to provide historical perspectives which have been useful in documenting land use-land cover change in specific times and places (Perz, 2007).

More importantly, although space is important in deforestation (Chomitz and Gray, 1996), only a few studies have mentioned the importance of distance (Mamingi et al., 1996; Chomitz and Gray, 1996). Those studies refer to the simple Euclidian distance, which is embedded in their proxy for distance[2] from the areas being deforested to the nearest markets or transportation infrastructure such as road density (Kaimowitz and Angelsen, 1998). Arguably, such models are suited to predict where deforestation will take place.

While existing studies provide useful analyses on deforestation, none of these studies have focused on the spatial determinants as driving forces behind deforestation. This study aims to contribute to the existing literature by examining the influence of social interactions on forest clearing in Sub-Sahara Africa.

The rest of the paper proceeds as follows. Section 1 provides a brief description of the causes of deforestation through the lens of the existing literature. Section 2 presents the methodological framework. Section 3 discusses the regression results; and the final section concludes.

1. Causes of deforestation

Deforestation is a serious form of environmental degradation which results in permanent loss of species, soil degradation, and changes in climate conditions through both biogeochemical and biogeophys-

[1] This is the argument they advance in support of their approach.
[2] One exception is the paper by Pan, Carr, Barbieri, Bilsborrow, and Suchindran (2007) who study forest clearing in the Ecuadorian Amazon.

ical processes (Davin and Noblet-Ducoudre, 2010). Empirical studies have sought to investigate the underlying factors of rapid forest loss in the tropical regions, and several reasons have been identified. Deforestation is most common in developing countries because of the strong ties between human welfare, economic development and dependence on natural resources (Culas, 2007). Naoto (2006) soberly argues that between 1990 and 2000 Africa, Latin America, and Asia had deforestation rates of about 0.8%, 0.4%, and 0.1%, respectively. Culas (2007) believes that, in many low-income countries, high population density and extreme poverty are the prime factors that exacerbate deforestation due to the increased demand for forest and agricultural goods. However, the existing literature presents conflicting evidence on the relationship between income and deforestation rate (Shafik, 1994; Dasgupta, Laplante, Wang and Wheeler, 2002). Chase (1993), Kaimowitz and Angelsen, (1998) argue that higher incomes mean greater demand for agricultural and forest goods which puts pressure on forest cover, and on the other hand, they are also associated with less demand for fuel, more capital-intensive agriculture and more off-farm employment opportunities, thus preserving forest areas. But the Environmental Kuznets Curve (EKC), hypothesized by some authors (Bhattarai and Hammig, 2002) to support the correlation between the level of income and environmental degradation, stipulates that the first effect is more common at low levels of development up to a certain income threshold (Martinez et al., 2002). For example, Martinez and co-authors, whose findings are consistent with the EKC hypothesis, argue that deforestation increases as the level of income increases up to some point, and then as people become wealthier, they move away from the exploitation of natural resources and therefore cause less damage to the ecosystem. The existence of the EKC also finds support in the findings by Shandra (2007) who points out that the process of economic development is strongly related to deforestation. His results indicate that in the early stage of development, economic activities require the use of natural resources because of the lack of heavy industries. But as a country becomes industrialized, there is a shift away from the use of natural resources followed by an increase of services and energy efficiency, hence a supposed reduction in the rate of deforestation. Admittedly, the EKC hypothesis has gained prominence since the seminal work of Grossman and Krueger (1993).

In addition to income, other driving forces that stimulate forest clearing have been identified. For example, Allen and Douglas (1985) show that the causes of deforestation stem mainly from a high population growth (deforestation for domestic use) and international trade (exports of wood). Furthermore, Ricardo (2001) concludes that educated people are more likely to preserve the environment as compared to uneducated ones.

As the quest on the cause of deforestation still remains unanswered, some researchers including Bohn and Deacon (2000), Ferreira (2004), and Mendelsohn (1994) argue that the high deforestation rates observed in developing countries are linked to their weak institutions, reasoning that poorly-defined property rights encourage a misuse of forest cover. Barbier (2002) shows how the presence of formal and informal institution not only safeguards the access, but also guarantees the optimal use of an open access such as forest. Ferreira (2004) also links deforestation to the lack of well-defined institutions and concludes that weak institutions in developing countries do not allow well defined property rights which leads to an overexploitation of natural resources.

Other researchers try to link deforestation to the level of trade – openness. For example, Humphreys (2004) notices that deforestation is the result of incursions by multinational firms and national economic interests. He posits that the structural adjustment programs imposed by the International Monetary Fund (IMF) on developing countries aggravate their external debts which lead to an increase in the gap between rich and poor nations. As a result, rural populations in poor countries are faced with limited employment opportunities, and the readily available option to them is to cut down trees in order to expand their farmlands. This view of trade fostering deforestation in a resource scarce environment is also shared by Naoto (2006). In contrast, Lopez and Galinato (2005) find mixed evidence about trade being a cause of deforestation. Using a micro-level approach, they establish three direct causes of deforestation, namely the access to roads and other infrastructure, poverty, and the expansion of the agricultural sector. They further identify income, trade-openness, macroeconomic policies, population and geographic conditions as factors affecting in turn the immediate causes of deforestation. The focus of their study is the impact of trade and economic growth on forest areas in Brazil, Indonesia, Malaysia and Philippines. They conclude that income has a large adverse impact on forest cover in all four countries, but the net effect of trade is small and ambiguous.

With respect to African countries, the majority of the existing literature considers deforestation to be an economic problem. As mentioned by Asiedu (2004), about 48 percent of the region's population lives on less than one dollar a day. Assuming that those countries will engage in a pathway conducive to economic growth, they will intensify their consumption of natural resources which will call for environmental concerns.

Additionally, several studies (IPCC, 2001 among others) argue that African countries will bear most of the adverse impacts of climate change for they have few mitigation techniques at their disposal. However, there is a general consensus that forest sinks are a valuable mitigation option. Tavoni, Sohngen and Bossetti (2007) find that forestry has a profound effect on the carbon market. Their estimates suggest that forest sinks can contribute to one third of total abatement by 2050 and induce a 40 percent decline in the price of carbon by the same year. Though, they acknowledge that the outcome is possible only if the tropical countries can put an end to deforestation in the first half of the 21st century or later given that countries commit to afforestation and better forest management thereafter. This significant carbon-forest linkage is also found in studies by Sohngen and Mendelsohn (2003), and Van't Veld and Plantinga (2005). Nevertheless, African countries should see the incentives to preserve their forest areas for, as reviewed in the third assessment of IPCC (2001), forestry provides many opportunities for low-cost carbon sequestration. Admittedly, fighting global warming requires more than planting trees. For example, technological innovations geared toward energy efficiency to reduce greenhouse gas emissions could supplement reforestation.

2. Data and methodology

This paper examines the determinants of deforestation in 24 Sub-Saharan African (SSA) countries (see Table 1 for a list of countries included in this study). We focus on developing countries rather than all nations of the world because net deforestation is more pronounced in developing nations. Furthermore, the narrow focus on SSA countries is motivated by the existence of ethnic diversity, a singular characteristic of SSA countries and the focus of this study.

Table 1. List of the countries

Country	Location	Colonial origin	Country	Location	Colonial origin
Angola	South	Portuguese	Guinea-Bissau	West	Portuguese
Botswana	South	British	Kenya	East	British
Burkina Faso	West	French	Malawi	South	British
Cameroon	Central	French	Mali	West	French
Central African Rep.	Central	French	Mozambique	South	Portuguese
Chad	Central	French	Senegal	West	French
Congo	Central	French	Sierra Leone	West	British
RDC	Central	Belgium	Sudan	Central	British
Equatorial Guinea	Central	Spanish	Tanzania	East	British
Gabon	Central	French	Uganda	East	British
Ghana	West	British	Zambia	South	British
Guinea	West	French	Zimbabwe	South	British

Source: CIA Workbook.

The sample of countries was selected based on the existence of net deforestation throughout the period from 1990 to 2004. Furthermore, data availability constrained the choice of the period.

The data used to compute the deforestation rates are derived from the FAOSTAT website. Admittedly, the FAO forest data have been criticized because of the extrapolation used to fill in some missing values. However, not only is a better source of deforestation data hard to find but deforestation rates are not available for African countries. More importantly, these shortcomings should not undermine the validity of our results. Another issue is the fact that we delineate our unit of observations to country level. Arguably, deforestation should not be considered at a national scale because it often takes place more locally. Though, the use of appropriate econometrics techniques should address the plausible country-specific measurement errors. We assume that spatial econometrics will help lessen the issue of mismeasurement since aggregate spatial data are characterized by spatial dependence (Anselin, 1988).

Table 2. Descriptive statistics

Variables	N	Mean	Maximum	Minimum	St. dev.
Deforestation rate	360	0.756	2.327	0.046	0.534
Per capita external debt	360	3.455	28.928	0	3.736
Agricultural price	360	0.0078	0.0748	0.000	0.0145
Pop density	360	32.852	142.200	1.722	32.111
Policy index	360	-0.987	9.000	-9.000	5.372
Income	360	770.160	7756.420	81.009	1176.603
Income squared	360	1973849	986.647	10.222	79.790

Following the literature review, the set of explanatory variables, the (n x n) matrix X as defined in models 5, 6, and 7, includes:

- *Income.* We use the per capita gross domestic product (PCGDP) and the square of per capita gross domestic product (PCGDPS) to account for the inverted U-shaped relationship (EKC) claimed to exist by previous studies (Culas, 2007) with respect to deforestation and income level in developing countries. The implication is that at a low level of development, an increase in income results in more demand of forest products, but the rate of deforestation is reduced beyond a certain level of income. However, this EKC is just a reflection of the mixed results presented by previous studies (Kaimowitz and Angelsen, 1998). Data on PCGDP are from the World Development Indicators, the online World Bank database.
- *Population density* (*POP*). This is seen by many researchers as the single most important cause of deforestation. A high population density means an increase in the pressure to find more space, food, and forest products such as fuel wood and timber. However, the empirical evidence of the positive correlation between population and deforestation is weak. For example, using country-level data from 1978 to 1988 to study the determinants of deforestation in the Brazilian Amazon, Pfaff (1997) finds that population density is significant only when it is the sole explanatory variable. This mixed signal of the association between deforestation and population is also evident in the work by Deacon (1994). His results suggest that only lagged, not the contemporaneous, population growth positively affects deforestation. The results become inconclusive when other explanatory variables are included or high income countries are excluded from the regressions. We derive the population density data from the World Development Indicators. The World Bank defines population density as midyear population divided by land area in square kilometers.
- *Institutions*. Past studies argue that institutional structures act as a deterrent to deforestation. The implementation of forest management requires the development of institutional mechanisms that value scarcity[1]. However, in developing countries, government very often lacks power, is unstable, and does not have popular support to enforce property rights (Angelsen and Kaimowitz, 1999). To assess the effectiveness of the institution governing a country, we use a composite index known as "combined policy score", a variable taken from the World Development Indicators. This index accounts for government effectiveness, rule of law, and political stability. Its values range from +9 to -9, with high positive values indicating better governance.
- *External debt per capita.* A common characteristic of developing countries is their huge external debt. Capistrano and Kiker (1995) argue that debt service has a significant influence on the depletion of tropical forests. The intuition is that countries have to engage in export-oriented policies in order to pay their external debt service. Those export-oriented policies encourage more production of forest goods or the expansion of agricultural land for cash crops (Capistrano and Kiker, 1995). To measure the external debt per capita, we use data from the World Development Indicators to compute the ratio of the total external debt by total population. The World Bank defines total external debt as the sum of public, publicly guaranteed, and private nonguaranteed long-term debt, use of IMF credit, and short-term debt.
- *Agricultural price.* Several researchers (Capistrano and Kiker, 1995; Angelsen and Kaimowitz, 1999; Arcand et al., 2008) agree that there is substantial evidence to support that high agricultural prices, and improved terms of trade and real exchange rates stimulate the conversion of forests to other uses. However, microeconomics evidence suggests that the theoretical explanation depends on farmers' preferences. If they opt for subsistence farming, then the trade-off between leisure and work implies the minimal consumption needs are easily reached even with high agricultural prices. Therefore, farmers do not need to clear forest to extend their agricultural land. In contrast, if farmers are profit maximizers, then high prices turn agriculture into a lucrative business, and farmers shift resources into deforestation to have more land dedicated to the production of commercial agricultural products. The agricultural price variable is the ratio of the export value of agricultural products to GDP. The values of agricultural products, expressed in thousands of U.S. dollar, are derived from the FAOSTAT website.

This paper models social interactions as a driving force behind forest clearing. Social interactions arise when economic agents, individually or collectively, affect each other's decisions. According to Ioannides and Topa (2010), social interactions emerge as a natural action when individuals share a common resource or space. And social interactions have been identified as the main causes of peer group effect, a phenomenon that an individual's choices are correlated with the choices of his peers (Cooper and Rege, 2011).

[1] One can rightfully argue that forest is a scarce resource.

Our prime hypothesis is that same-ethnic interactions may account for the driving forces behind the high rates of deforestation in SSA. SSA countries are characterized by ethnic diversity, and an ethnic group within a given country may have its members scattered throughout neighboring countries. Furthermore, if deforestation rates in country i are correlated with deforestation rates in country j as a result of same-ethnic interactions, then this potential spatial clustering is defined as follows (Anselin and Bera, 1998):

$$\text{Cov}(y_i, y_j) = E(y_i, y_j) - E(y_i)E(y_j) \neq 0 \quad \text{for } i \neq j, \tag{1}$$

where y_i and y_j are deforestation rates in country i and j, respectively.

The spatial clustering pattern can be identified by means of Moran's I test. The Moran's I statistic is given by:

$$I = [n/S_0]^* \,[(z' Wz) \,/\, (z'z)], \tag{2}$$

where z is an (n x 1) vector of observations expressed as deviations from the mean $\left(x_i - \overline{x}\right)$, with x_i being the i^{th} observation and $\overline{x} = \frac{\sum_1^n x_i}{N}$; S is a standardization factor defined as:

$$S_o = \sum_{i=1}^{i=n}\sum_{j=1}^{j=n} w_{ij}. \tag{3}$$

W is an (n x n) spatial row-normalized weight matrix with elements w_{ij} defined as:

$$S_o = \sum_{i=1}^{i=n} w_{ij} = 1 \text{ for each row.} \tag{4}$$

In this paper, the weight matrix is the first order spatial contiguity matrix. This contiguity matrix captures the interactions between members of any ethnic group scattered across neighboring countries. This interaction is facilitated through the socio-cultural background[1] common to ethnic groups in any two neighboring countries. The elements of the matrix are such that they are equal to 1 for any two countries sharing a common border, and 0 when they do not. Since a country cannot be its own neighbor, the elements on the main diagonal are all set to zero. The spatial weight matrix is further row-normalized, which means that the elements of each row are transformed in such a way that they must sum to one (see equation (4)).

One should pursue the spatial modeling in accordance with the statistical inferences based on values of Moran's I. Moran's I statistic is a correlation coefficient, with high positive (negative) values indicating positive (negative) spatial correlation. Specifically, values close to negative 1 mean perfect dispersion, values close to 1 indicate perfect correlation, and zero values are a random spatial pattern (Florax, Flomer, and Rey, 2003).

Spatial process models take different forms depending on the interpretations of the spatial dependence. If the theoretical interpretation favors spatial interaction, then a spatial lag model is in order. It is expressed as:

$$y = \lambda Wy + X\beta + €, \quad € \sim N(0, \sigma^2 I_n), \tag{5}$$

where y is an (n x 1) vector of deforestation rates; X is an (n x k) matrix of explanatory variables, including agricultural price, per capita external debt, policy index, population density, income and income squared; λ is a spatial lag parameter; β, a (k x 1) are the vectors of trend parameters; and W is the spatial row-normalized weight matrix defined as above. According to Anselin (1988), due to the correlation between the spatial variable and the error term, the ordinary least squares estimators of the spatial lag model are biased and inconsistent, regardless of the properties of the error term.

However, if the researcher believes that the spatial dependence stems from omitted variables that are related to each other over space, then he will favor a spatial error model defined as follows:

$$y = X\beta + \mu, \quad \mu = \rho W\mu + €, \quad € \sim N(0, \sigma^2 I_n), \tag{6}$$

where y, X, β and W are defined as in equation (5); and ρ is a spatial autoregressive parameter.

Due to the non-diagonal structure of the matrix of variance-covariance of the error term, the application of the ordinary least squares to the regression of model (6) yields unbiased but inefficient results (Anselin, 1988).

Models (5) and (6) are special cases of a general model known as spatial autocorrelation model represented by:

$$y = \lambda Wy + X\beta + \mu, \quad \mu = \rho W\mu + €, \quad € \sim N(0, \sigma^2 I_n), \tag{7}$$

where y, X, β, ρ, λ and W are defined as in equations (5) and (6).

The spatial dependence enters equation (7) through both the dependent variable and the error term. By setting $\lambda = 0$, equation (7) collapses to equation (6). Alternatively, equation (7) yields equation (5) by restricting $\rho = 0$. Finally, the lack of spatial correlation is depicted by simultaneously forcing $\lambda = \rho = 0$.

[1] Examples are religions, dialects, or family ties.

To address the issues of inefficiency and biasness pointed out by Anselin (1988), Kelijian and Prucha (1998) have proposed a generalized spatial two-stage least squares (GS-2SLS) approach for estimating the parameters of model[1] (7). The approach involves a three-step procedure. In the first step, equation (7) is estimated by two-stage least squares (2SLS). In the second step, the autoregressive parameter ρ is estimated by generalized method of moments (GMM). According to Kelijian and Prucha, GMM yields a consistent estimator of ρ, whether or not the weight matrices for the dependent variable and the error term are equal. Finally, equation (7) is re-estimated by 2SLS after transforming the model using the Cochrane-Orcutt approach as follows.

First, rewrite equation (7) as:

$$y = Z\delta + \mu,$$

$$\mu = \rho W\mu + €, \tag{8}$$

where y, X, ρ and W are defined as in equations (5), (6) and (7); $Z = (X, Wy)$ and $\delta = (\beta', \lambda)'$.

A Cochrane-Orcutt transformation yields the following (Kelijian and Prucha, 1998):

$$y^* = Z^*\delta + €, \tag{9}$$

where $y^* = y - \rho Wy$ and $Z^* = Z - \rho WZ$.

We expect that an increase in income will increase deforestation up to some point and then decline because developing countries rely heavily on the exploitation of natural resources. Thus, we expect the sign on the coefficient estimate for income to be positive and that for income squared to be negative in accordance with the EKC hypothesis. We expect population density to be positive, because it tells a lot about the pressure exerted on land areas. As in many other previous studies, we expect the sign of the coefficient estimate for agricultural price variable to be positive because higher agricultural prices are an incentive to clear forest for agricultural use. Finally, we expect the coefficient estimate for policy variable, the proxy for institutional quality, to be positive because good governance should be a deterrent to deforestation.

3. Results

We first fit equation (7) by imposing the restrictions[2] $\lambda = \rho = 0$, then we re-estimate the model by relaxing these restrictions[3]. The rationale behind this procedure is to assess the effect on deforestation rates when spatial correlation is not accounted for, an approach used by the majority of previous studies. As in Culas (2007), we first run fixed effects (see Table 3) and random effects (see Table 4), and then apply the Hausman test to determine the appropriate model to consider in the case of linear panel data. The results of the Hausman test are presented in Table 5. The Hausman test favors fixed effects over random effects. The fixed effects results indicate that all the variables included in the regression are statistically significant except the per capita external debt.

Table 3. Fixed effects

Variable	Coefficient	T-statistics
Constant	0.482	4.903*
External debt	5.38E-05	0.835
Agricultural price	0.478	3.230*
Population density	0.00644	13.974*
Institutions	-0.00112	-1.926***
Income	2.93E-05	5.803*
Income squared	-1.88E-09	-3.578*

Note: *, **, and *** denote statistically significant at 1 percent, 5 percent, and 10 percent respectively.

Table 4. Random effects

Variable	Coefficient	T-statistics
Constant	0.481	4.903*
External debt	4.80E-05	0.718
Agricultural price	0.432	2.218**
Population density	0.00653	18.802*
Institutions	-0.00118	-2.274**
Income	2.82E-05	5.852*
Income squared	-1.78E-09	-3.161*

Note: *, **, and *** denote statistically significant at 1 percent, 5 percent, and 10 percent, respectively.

Table 5. Hausman test

Variable	Fixed	Random	Var. (diff.)	Prob.
External debt	0.000054	0.000048	0.000000	0.321
Agricultural price	0.478	0.432	0.00229	0.336
Population density	0.00644	0.00653	0.000000	0.332
Institutions	-0.00112	-0.00118	0.000000	0.433
Income	0.000029	0.000028	0.000000	0.633
Income squared	-0.000000	-0.000000	0.000000	0.705

Confirming our apriori expectations, the coefficient on agricultural price variable indicates that a 10 percent increase in agricultural prices leads to a 4.77 percent statistically significant increase in deforestation rates. This result is in line with previous studies. Barbier and Burgess (2001) and Angelsen and Kaimowitz (1999) also find commodity trade to be a significant determinant of deforestation in developing countries. Moreover, these results echo past studies (Stern, Common and Barbier, 1996; Bhattarai and Hamming, 2002) vis-à-vis the existence of the inverted U-shaped between deforestation and income level in developing countries. This means that deforestation accelerates with an increase in per capita income, and then the trend reverses itself at a higher level of income. In their paper, Bhattarai and

[1] Maximum likelihood estimation has also been used. It is not too practical because of its computational difficulties.
[2] Results of which will yield fixed effects and random effects.
[3] To test the spatial correlation.

Hamming (2002) identify the EKC turning point to be somewhere between $5000 and $7000. In contrast, the results by Arcand et al. (2008) do not support the existence of the EKC.

The statistically positive sign of the coefficient on the population density variable[1] comes without surprise because higher population density means greater pressure to find more spaces for habitat. In developing countries, forest areas are easier to transform into housing developments compared to mountain areas or desert regions because cutting trees requires little or no machinery. In addition, it is well-known that SSA countries have a very high rate of population growth and also a significant share of the population is employed in the agricultural sector, a combination of factors that will cause the agricultural labor force to expand (Vyas and Casley, 1988). Furthermore, the increase in the agricultural labor supply will exert a pressure on forest cover into degradation. Bawa and Dayanandan (1997) reach a similar conclusion. In effect, they find population density to have the greatest effect on deforestation in Africa. And the most important aspect of their results is that deforestation rate is more strongly correlated with rural population than with urban population.

All else equal, the negative coefficient on the policy variable attributes the high rate of deforestation to the poorly defined property rights in the region, findings corroborated by previous studies (Awung, 1998).

Admittedly, the fixed effects approach in its simple form does not take care of the spatial correlation that is a natural part of deforestation. A comparison of the simple linear panel model and the spatial model allows one to highlight the significance of social interaction effects when an economic agent's choices to clear forest cover are influenced by others in his surroundings and who are taking the same decisions.

The results of the spatial model (equation (7)) are shown in Table 6. The estimation of equation (7) can be carried out either with a maximum likelihood (ML) approach or a generalized spatial two-stage least squares (GS-2SLS) techniques. The ML approach assumes normality, while the GS-2SLS estimates are robust to non-normality (Chong, Phipps, and Anselin, 2001), which make them superior. To obtain the appropriate effect of a change in the explanatory variables on the dependent variable, Chong et al. (2001) show that the coefficients in the spatial model needs to be multiplied by $(1/(1-\lambda))$.

Table 6. Spatial two-stage least squares results for SSA

	2SLS		GS-2SLS	
Variable	Coefficient	T-ratio	Coefficient	T-ratio
External debt	-0.0139	-2.535**	-0.0161	-2.896***
Ag. price	-10.641	-5.775**	-11.628	-6.367***
Pop. density	0.00959	13.744***	0.00951	12.968***
Institutions	-0.00454	-1.127	-0.00658	-1.738*
Income	0.000213	3.225***	0.000307	4.716***
Income squared	-2.820E-8	-2.379**	-3.899 E-8	-3.276***
Lamda (λ)	0.795	9.988***	0.534	5.231***
Constant	-0.541	-6.479***	-0.196	-1.501

Notes: ***, ** and * indicate that the parameter is statistically significant at 1%, 5% and 10% levels, respectively.

Three main observations emerge when comparing the results with the restrictions $\rho = \lambda = 0$ to the alternative hypothesis. First, the spatial autoregressive coefficients for agricultural price, per capita external debt and policy variables turn negative. The negative coefficient on policy variable indicates that strong institutions are effective in haltering forest clearing, and most importantly illegal logging. This result corroborates the findings by Arcand et al. (2008) who also find better institutions to curtail deforestation. The statistically negative coefficient on agricultural price is an indication that global economic incentives are a powerful driving force of deforestation. The fiscally pressured African countries turn to the increasingly globalized market for forestry products to raise revenues. The negative association between per capita external debt and deforestation suggests that countries that do not have access to external debt are more likely to engage in export of forestry products. The idea is further reinforced by the statistically negative coefficient on agricultural price. Humphreys (2004) reaches a similar conclusion, arguing that in poor and highly indebted countries, farmers with very little off-farm employment opportunities have no other choice but to convert forests into farmlands.

A second important point worth mentioning is that the magnitudes of the coefficient estimates on the variables in the GS-2SLS are much larger in absolute values than the simple linear fixed effect estimates. It becomes clear that estimations that ignore the spatial correlation tend to not only yield conflicting signs on the coefficient estimates but also underestimate the magnitude of the effects of the determinants of deforestations. An edifying example can be found in

[1] Ferreira (2004) finds similar results.

Culas (2007) who use a simple panel data to analyze deforestation in selected Asian Latin American and African countries. His results are statistically insignificant for the African sample. In other words, the failure to account for the spatial determinants of deforestation could seriously undermine the validity of previous studies.

The third observation, more important, is the fact that the estimated λ is positive and statistically significant. This suggests that if deforestation rate is high in one country, it will be high in the neighboring countries as well. The estimated value of 0.534 for λ indicates that deforestation rate in one country, on average, is equal to 53.4 percent of the weighted average of surrounding countries' deforestation rates. This third observation underpins the significance of neighborhood effects on the decision to deplete forest covers.

Although one may rightfully argue that the SSA countries share some similarities in terms of their level of economic development, it remains true that those countries are different in terms of their cultural and social background. For example, while the Bantus populate most of Southern Africa, they are entirely absent in West Africa. The converse is true regarding the Hausa or Bambara ethnic groups. Thus, insightful information can also be gained by examining the spatial determinants of deforestation by sub-regional groups. Bawa and Dayanandan (1997) surmise the most significant causes of deforestation to be region specific. We further sort the 24 countries according to their geographic locations to form 4 regions, namely West Africa, East Africa, Central Africa, and Southern Africa. Each sub-group represents a hub of a specific set of ethnic groups. Apart from the ethnic specificity, the sub-groups have a different colonial background. For example, while West Africa and Central Africa were predominantly French colonies, East Africa and Southern Africa were under the British rules. The regression results based on sub-regional characteristics are presented in Tables 7 and 8. The disaggregated results show dissimilarities among the different sub-regions. Tables 7 and 8 suggest that the determinants of deforestation in Central Africa are best described using model 6, while model 7 best suits East, Southern, and West Africa. Additionally, the contribution of individual variables also differs among the four regions in terms of magnitudes, signs and statistical significance.

Table 7. Spatial two-stage least squares results by region

	Central	East	South	West
Variable	Coefficient	Coefficient	Coefficient	Coefficient
Per capita external debt	-0.0143 (-2.62)***	-0.0665 (-5.99)***	-0.0166 (-2.01)**	-0.0117 (-0.97)
Agricultural price	-3.819 (-2.559)***	-125.14 (-4.37)***	146.11 (5.44)***	83.46 (7.19)***
Pop. density	0.0278 (6.96)***	0.00256 (1.81)*	-0.00222 (-1.06)	0.00711 (5.48)***
Institutions	-0.0241 (-3.60)***	0.00573 (0.556)	0.00646 (0.849)	0.00612 (1.30)
Income	-8.76E-5 (-1.35)	0.00705 (3.11)***	-0.000232 (-1.115)	0.0138 (7.44)***
Income squared	9.99 E-9 (1.01)	-7.69 E-6 (-2.41)**	5.998 E-8 (1.18)	-2.426 E-5 (-8.06)***
Lamda (λ)	0.456 (0.77)	-0.858 (-2.25)**	1.924 (4.02)***	-1.19 (-3.92)***
Constant	0.749 (2.10)**	-0.276 (-0.82)	-1.31 (-3.07)***	-0.418 (-4.15)***

Notes: ***, ** and * indicate that the parameter is statistically significant at 1%, 5% and 10% levels, respectively. The *t*-ratios are in parentheses.

Table 8. GMM estimate of rho

	SSA	Central	East	South	West
Rho	-0.429	0.960	-0.331	-0.483	-0.143
Sigma	0.387	0.233	0.0858	0.338	0.219
95 % confidence interval	-0.469 to -0.389	0.919 to 1.002	-0.356 to -0.306	-0.490 to -0.475	-0.184 to -0.101

Specifically, one should note the following:

1. *Per capita external debt*. This variable seems to explain forest clearing in all but the West African region. This result suggests that deforestation is driven probably for the purpose of agricultural land extension in West African countries. Similar to the SSA results, the estimated coefficient for the variable per capita external debt is negative and statistically significant in South, East, and Central Africa. With respect to the magnitude of the coefficient, it is four times larger for the Eastern African countries compared to the remaining two regions.

2. *Income*. The results presented in Table 7 show that the environmental Kuznets curve appears to exist only in East and West Africa. As for Central and Southern Africa, the estimated coefficients for the variables income and income squared have the expected sign, but are not statistically significant.
3. *Institutions.* As evidenced by the coefficient of the political institutions variable (policy), the quality of institutions in explaining deforestation matters only in Central African countries.
4. *Agricultural price*. The estimated coefficient for this variable is quite intriguing. In West and Southern Africa, the increase in the prices of agricultural products stimulates forest clearing. The converse is true in Central and East Africa. Another singularity with the variable is its large coefficient estimates for the East, South and West regions. A closer look at the coefficient estimates for external debt and agricultural price points to the existence of global economic incentives for forest clearing in SSA countries.
5. *Population density*. The coefficient associated with population density is positive and statistically significant in all but the Southern Africa's sample. This result comes without any surprise since most Southern African countries were characterized by a pronounced land inequality which led to land reform policies implemented by their respective governments.

Conclusion

The primary purpose of this paper is to assess the effects of social interactions on deforestation in Sub-Saharan Africa during 1990-2004 period. The results of this study suggest that deforestation in one country is positively related to deforestation in neighboring countries, maybe because of interactions among economic agents in adjacent countries or because of global economic incentives that encourage forest clearing.

These findings warrant the use of appropriate spatial models, not just using the Euclidian distance as one of the explanatory variables, when analyzing the determinants of deforestation if one's objective is to obtain accurate coefficient estimates. Our results show that the failure to incorporate spatial dependence (ignoring social interactions when studying deforestation at the country level) could undermine the validity of the study.

In addition, we find enough evidence to conclude that the prices of agricultural products, external debt, and quality of institutions tend to curtail the pace of forest clearing while a low level of income and high population density encourage deforestation in Sub-Saharan Africa. Furthermore, the sub-regional results suggest that the effects of the determinants of forest clearing in SSA are region specific. For example, while the quality of institutions is a deterrent to deforestation only in the central region, access to external debt appears to reduce forest clearing in all but the western part of SSA.

Finally, these results have considerable policy implications. Since interactions among economic agents in neighboring countries explain in most part the high rate of deforestation in SSA, policy makers are strongly encouraged to coordinate their actions in order to come up with a regional approach in halting forest clearings.

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